MentaLex: a Mental Processes Lexicon based on the Essay dataset*

Maria Aráujo Barbosa[1], Ricardo Queiroz[2], Luis Brito[2], Francisco S. Marcondes[1], Adelino Gala[3], and Dalila Durães[1]

[1] Algoritmi Centre, University of Minho, Braga, Portugal
[2] Portucalense University, Porto, Portugal
[3] Digimedia, University of Aveiro, Aveiro, Portugal
pg42844@alunos.uminho.pt, {44830, 44881}@alunos.upt.pt, adelino@ua.pt,
{francisco.marcondes, dalila.duraes}@algoritmi.uminho.pt

Abstract. Considering that the performance of personality predictors are not consistently increasing throughout the years, as an alternative, the idea was to provide big5 personality traits lexicon based on the Essay dataset. However, it was eventually realized that three personalities wordset were overlapped requiring a change of course. The research changed the underlying model from big5 to Vann Joines' mental processes as it appear to suit better with the empirical findings. The resulting lexicon dataset is composed with 3432 commonly used words and 3639 avoided prone words for each mental process. The commonly used words are capable of covering 81% of the Twitter Personality dataset.

Keywords: Mental Processes · lexicon · personality · NLP

1 Introduction

Personality is an important aspect of life and plays a decisive role in how people behave in different scenarios, determining patterns of thinking, acting, personal and social individuality. These aspects can be seen in the writing or speaking style, and in other aspects of an individual social life [1]. Like language, writing is also something unique in every person. In another perspective, an analysis of the frequency of words can identify letters written by soldiers, the speeches of politicians and also identify the authors of literary works [2].

The patterns that identify an individual are a qualitative metric to define personality such as Allport's theory of traits, the 16-factor Cattell's model, Vann Joines' mental traits [3], the Myers-Briggs Type Indicator (MBTI) and the Big Five (big5) [4]. This paper is centered in big5 and Joines' mental processes.

2 Related work

The current state of the art in big5 personality trait detection can be illustrated by a table depicted in figure 1. Similar numbers are presented in other surveys

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[5,6,7] and papers [8,9,10]. In short, the average scores ranges on 60% except for Ren *et al.* [11] that appears as an outlier with an strategy based on BERT with SenticNet on CNN (it was not possible to easily find the code for reproduction).

Method	**F-measure**						**Accuracy**					
	Opn	**Con**	**Ext**	**Agr**	**Neu**	**Avg**	**Opn**	**Con**	**Ext**	**Agr**	**Neu**	**Avg**
Xue et al. [20]	**67.84**	**63.46**	**71.50**	**71.92**	62.36	67.416	63.16	57.49	58.91	57.49	59.51	59.312
Ren et al. [75]							**80.35**	**80.23**	**79.94**	**80.30**	**80.14**	**80.192**
Ramezani et al. [18]	57.37	59.74	65.80	61.62	60.69	61.04	56.30	59.18	64.25	60.31	61.14	60.24
Wang et al. [62]	67	68	67	69	**69**	**68**	64.80	59.10	60	57.70	63	60.92
Jiang et al. [69]							65.86	58.55	60.62	59.72	61.04	61.158
Mehta et al. [70]							64.6	59.2	60	58.8	60.5	60.62
Kazameini et al. [74]							62.09	57.84	59.30	56.52	59.39	59.028
Majumder et al. [65]							62.68	57.30	58.09	56.71	59.38	58.832
Tighe et al. [55]	61.9	56	55.6	55.7	58.3	57.7	61.95	56.04	55.75	57.54	58.31	57.918
Verhoeven et al. [53]	56	54	53	50	54	53.4						
Poria et al. [51]	66.1	63.3	63.4	61.5	63.7	63.6						
Mohammad and Kiritchenko [87]	60.57	56.46	56.28	53.9	58.15	57.072						

Fig. 1: The state of the art in personality detection [7]

The Essays dataset [2] is being studied for 20 years and the prediction values have not yet increased consistently [6]. This paper approach is then a step back and, instead of trying to develop a new predictor, to build a lexicon. This is inspired by the EmoLex [12,13] that can be considered a gold standard for emotion detection and has been used for around 10 years with more than 1000 citations on each paper. It is expected that a lexicon as such may provide, at least, useful insights for advancing the state of the art.

In 2010, Tal Yarkoni [14] conducted a thorough examination of the personalities and words used in 694 blogs posts. He performs a big5 questionnaire to the authors in order to categorise their personalities. The outcomes included a summary of the relationships between the Big Five traits and the 20 words that were more represent each trait. However, there is no information regarding a potential lexicon developed from the study's results. Since then, no significant research on the creation of personality lexicons has been found.

3 Methodology

The Essays dataset [2] is composed of 2468 open topic essays written by people whose personality was already assessed. Therefore, together with each essay there are five personality traits (also called big5 as proposed by [4]) binary flagged.

A big5 assessment is made through a form from which the subject chooses a set of words that are considered most related to himself or herself [4]. Analogously, the hypothesis explored in this paper is that, the personality trait of a person would be revealed by the words chosen for creating a text. For testing this hypothesis, the tf/idf *cf.* [15] value is computed for each lemmatized word on each personality trait, excluding those whose tf/idf value is 0.0. That procedure, shown in algorithm 1, results in a lexicon with the words commonly chosen and not used words by each personality.

The deducing hypothesis is that a set of words is meaningful enough to provide at least a personality insight. For that claim to be true, the identified words shall be "insistently" used on different texts as a sort of "trail". For testing

Algorithm 1 Meaningful Words per Trait.

```
Require: Essay_Dataset ← pipe([lemmatize | remove stop words | standardize in lowercase | extract
   adjectives, verbs and nouns]).
   procedure getWordsFor(trait)
       trait_texts ← retrieveTextFor(trait, Essay_Dataset)
       TF/IDF ← computeTF/IDF(trait_texts)
       for word, tf/idf in TF/IDF do
           if tf/idf > 0 then
               Words ←+ word
           end if
       end for
       return Words
   end procedure
   for trait in big5 do
       Used_Lexicon ←+ getWordsFor(trait)
       Avoided_Lexicon ←+ getWordsFor(big5 - trait)
   end for
```

that deduced hypothesis, the Twitter Personality dataset [16] with 9879 tweets is used to verify how in-depth the resulting lexicon is. That dataset was chosen because in little texts the probability of a word happening is reduced compared to larger texts.

The use of the lexicon for classification lies outside the scope for this paper.

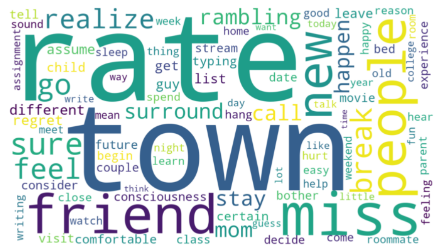
4 Results and Discussion

By the assessment made upon the Essays dataset it was not possible to find all the 5 personality traits. It was possible to distinguish agreeableness and neuroticism with almost disjoint word sets. However, the word-set for extroversion, openness and conscientiousness are overlapping (despite being almost disjoint with the other two). That experimental result may suggest that these three traits may be considered one when personality is abducted from open topic essays. An alternative cognition theory that suits better with these findings is the one proposed by [3] called "personality adaptations" (the relation between big5 and Personality Adaptations is presented in [4]).

Personality Adaptations theory suggests the existence of six mental processes, three of them primary and the other three secondary. Each person has at least one primary process and may or may not have a secondary one [3]. What is suggested is that the primary processes that are being revealed when someone writes a text. Accepting that suggestion, adapting from the Personality Adaptations theory, the primary processes would be: paranoid, schizoid and neuroticism. For a reference, the terms associated with the respective mental process and the unrelated words are presented as word-clouds in Figure 2, constructed directly by calculating the tf-idf value described in algorithm 1.

As can be noticed the number of words related to each mental process is actually small. To evaluate its suitability of the lexicon, the Twitter Personality dataset is used to verify how many tweets are composed by words that are in the lexicon (coverage analysis). The generated lexicon, composed by 276 words, presented a coverage of 69% in that dataset. As an attempt to increase the

(a) Neuroticism



(b) ¬Neuroticism

(c) Paranoid

(d) ¬Paranoid

(e) Schizoid

(f) ¬Schizoid

Fig. 2: Word-cloud that includes both the words connected to each mental process and the words that are not.

coverage the wordset, synonyms were retrieved resulting in a dataset with 3432 words covering 81% of the dataset. That coverage is considered sufficient due to the tweets' peculiarities; *i.e.* very short unstructured texts with misspelled words and slangs, eventually, with only a link or emoji. As an analogous procedure, upon the 316 words found to be avoided, their synonyms was gathered resulting into a lexicon of 3639 words.

For a summary, the lexicon characteristics are presented in tables 1 and 2.

	words	synonym	words & synonym	%	nouns	verbs	adj.
paranoid	87	1003	1090	32%	523	443	124
schizoid	53	762	815	24%	407	335	75
neuroticism	136	1391	1527	44%	793	560	174
total	276	3156	3432	100%	1723	1338	373
coverage	69%	–	81%	–	–	–	–

Table 1: Summary of commonly used words Lexicon

	words	synonym	words & synonym	%	nouns	verbs	adj.
¬paranoid	85	766	851	23%	399	125	327
¬schizoid	144	1554	1698	47%	827	235	636
¬neuroticism	87	1003	1090	30%	523	126	449
total	316	3323	3639	100%	1749	482	1408

Table 2: Summary of avoiding prone words Lexicon

Note for the Reviewers: During the review period the material related with this paper will available in google drive, please follow: `https://drive.google.com/drive/folders/1BU-UWZvXg5LOgLU3MNJqgrOOZf1fzlKW?usp=sharing`. In the camera ready version, this line will be replaced with a github repository.

5 Conclusion

The current study examines how individual personality traits connect to writing style. The Big5 and Personality Adaptations theories served as the study's scientific guidance in this aspect. The results allowed to identify three different traits. Based on the Adaption Personality theory, the authors believed identified the primary processes: paranoid, schizoid and neuroticism. The final generated lexicon contained 3432 commonly used words and 3639 avoiding prone words for each mental process (both including noun, verb, and adjectives).

For future works, it occurred to the authors that the verb tenses may embed additional personality information, therefore a reassessment but without lemmatization may be worthful. In addition, there was a glimpse that there could also be information in the stop-words, therefore, perhaps, an assessment using n-grams, therefore preserving some syntactic information, may also help in improving the lexicon.

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